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Submitted to: WAC 2002 Conference
Orlando, Florida
June 9-13, 2002

COMPARISON OF SOFT COMPUTING TECHNIQUES FOR A THREE-PHASE OIL FIELD CENTRIFUGE

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ABSTRACT

In this work we compare fuzzy techniques to neural network techniques for building a soft sensor for a three-phase oil field centrifuge. The soft sensor is used in a feed-forward control system that augments a feedback control system. Two approaches were used to develop the soft sensor. The first approach was to use a fuzzy rule based system based upon the experience of an expert operator. The expert operator's experience was supplemented using a computer model of the system. The second approach was to use a neural network to build the inverse of the computer model. The pros and cons of both techniques are discussed.

KEYWORDS: fuzzy logic, neural networks, soft sensor, soft computing

INTRODUCTION

The three-phase centrifuge [1] discussed here is a machine used by Centech, Inc. in oil fields and refineries to separate meta-stable emulsions consisting of oil and water stabilized by solids. These emulsions are normally disposed of as waste and sometimes hazardous waste. The centrifuge turns these wastes into clean, saleable oil, water that can be reused in operating processes and, solids that can be disposed of in landfills [2].

A fuzzy feedback control system [3,4] controls the quality of the products separated by the centrifuge. In addition, the centrifuge utilizes a fuzzy feed-forward control system [5] to monitor feed changes, anticipate corrective action that might be needed, and take the desired corrective action. The feed-forward control system is very important to the operation of the centrifuge because the feed can be highly variable due to settling and layering of phases in feed tanks and even weather conditions when feed comes from outdoor waste pits or ponds.

One important component of the feed-forward system is the sensor that measures the input variables for the controller. In this case the sensor is a soft sensor because two variables required for the controller cannot be measured directly. Variables that can be measured are used to compute values for the required controller input variables. The required controller input variables are: feed temperature (T_f), feed water content (ϕ_w), and feed solid content (ϕ_s). The variables that can be measured are: feed temperature (T_f), feed BS&W (basic solids and water) ($\phi_{sw}=\phi_s+\phi_w$), feed flow rate (F), and feed heater power requirement (P).

The feed BS&W change can be measured, but this value is the combined change of the water and solid in the feed. Based upon calculations and/or operator experience, changes in the feed flow rate and heater power requirements will indicate how much of the BS&W change is water and how much is solid (Viscosity changes affect flow through the positive-displacement feed pump and heat capacity and flow rate effect heater power requirements to maintain a temperature setpoint). Changes in the feed temperature will moderate the effect of the magnitude and possibly the direction of the changes in the feed flow and the heater power requirements. Therefore feed temperature change must be taken into account when using the soft sensor.

Two approaches were used to develop the soft sensor. The first approach was to use a fuzzy rule based system based upon the experience of an expert operator. The expert operator's experience was supplemented using a computer model of the system. The computer model could not be used directly for the soft sensor since it worked in reverse of the soft sensor. The second approach was to use a neural network to build the inverse of the computer model.

OPERATOR EXPERIENCE AND COMPUTER MODEL

Our expert had a great deal of experience with manual feed-forward control. He has been quite successful in the past determining the changes in both feed solid content and feed water content, by observing the total feed BS&W change in addition to changes in feed flow rate and feed heater power requirements. He was able to supply us with information to develop 45 fuzzy rules and their corresponding membership functions. These are essentially the rules that he has used in the past for his manual feed-forward control of the centrifuge. These rules were of the form:

If ΔF is … and $\Delta\phi_{sw}$ is … and ΔP is … Then $\Delta\phi_w$ is … and $\Delta\phi_s$ is …

Table I lists a subset of these rules. The membership functions were the simple triangle and trapezoidal shapes found commonly in fuzzy expert systems.

TABLE I. Abbreviated set of basic rules for the fuzzy soft sensor.

Rule	If ΔF is	and $\Delta\phi_{sw}$ is	and ΔP is	Then $\Delta\phi_w$ is	and $\Delta\phi_s$ is
1	Large Negative	Negative	Negative	Negative	Negative
2	Large Negative	Negative	Zero	Negative	Positive
• •	• •	• •	• •	• •	• •
19	Zero	Negative	Negative	Negative	Negative
• •	• •	• •	• •	• •	• •
44	Large Positive	Positive	Zero	Positive	Positive
45	Large Positive	Positive	Positive	Positive	Negative

Unfortunately, these rules only worked for about 85% of the possible cases. This is probably good enough if the expert operator is available for additional consulting, but not good enough for a totally automated system. Part of the problem is that we did not ask the right questions when we developed the rules from the expert's knowledge. We did not take into account that the feed properties, in particular viscosity, will change quite differently, depending upon which component, oil or water, is the dispersed phase and which component is the continuous phase. Adding this variable, plus further subdividing the input membership functions creates a significantly large number of rules. A set of rules this large is almost too large for any expert to define with great precision. So we wrote a computer model to describe the feed portion of the centrifuge system in order to help the expert extend the rule set described above and to fill in gaps that might be beyond the expert's experience. The model is based upon simple energy, mass and momentum balances for the feed system. Physical properties and physical property correlations were obtained from the literature for each component, oil, water, and solids, and for mixtures of the components.

The computer model takes as input the feed temperature and water and solids content at two different times ($T_{f,a}$, $T_{f,b}$, $\phi_{w,a}$, $\phi_{w,b}$, $\phi_{s,a}$, $\phi_{s,b}$) and computes the resulting change in feed flow rate and heater power requirement (ΔF, ΔP). The model also requires the following centrifuge operating parameters: fractional power to the feed pump, hydrostatic head on pump, API gravity (a measure of relative density) of the oil, heater efficiency, and the process temperature setpoint. Physical properties of the water, oil, and solids are also needed. These include density, heat capacity, and viscosity. These properties generally vary with temperature. The physical properties of the oil/water/solids emulsion also need to be estimated.

FUZZY LOGIC SOFT SENSOR

Every rule supplied by our expert had solid reasoning behind it; however, when we tested this system, all of our questions were not answered correctly. After running the computer program, it became obvious why. Forty-five rules are not comprehensive enough to cover every case.

There is enough information available to solve the problem. But in order to solve the problem, we had to break the input membership functions or input groups into smaller subgroups. For example, the input variable ΔP used in all of the rules had three membership functions. They were *Positive, Negative,* and *Zero*. Essentially, each of these membership functions needed to be further subdivided by three. This gives us nine membership functions for the variable ΔP. Doing this with all of the input variables allows us to take into account all possible combinations of water and solid that goes with one BS&W change. This, the inclusion of feed temperature changes, and a recognition of whether the oil or the water is the continuous phase, requires the use of many more rules.

In order to accomplish this with a reasonable effort, we use some "crisp" rules and a branch and bound technique to choose the rules that will be used for a given condition. We obtained 27 branch points from the original 45 rules. The desired branch point is chosen using "crisp" values of the input variables ΔF, $\Delta\phi_{sw}$, and ΔP. From the branch point we step to a unique fuzzy control routine that manages the fuzzy rules under that branch. The crisp rules used to choose between the 27 branch points are of the form:

If ΔF is … and $\Delta\phi_{sw}$ is … and ΔP is … Then *Go to (Fuzzy Soft Sensor X)*

Figure 1 is diagram showing the selection process for the fuzzy soft sensor method.

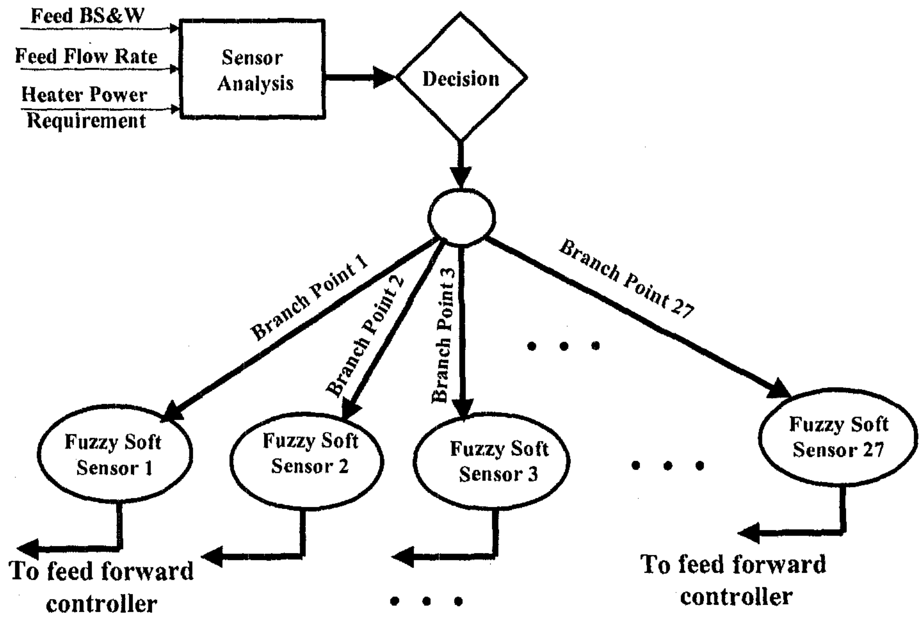

Figure 1. Diagram of the soft sensor branch and bound approach.

The soft sensors (1-27) are all different. Some are very simple and some are reasonably complicated, using many of the original 45 rules with modified membership functions. In addition to the variables shown above (ΔF, $\Delta\phi_{sw}$, and ΔP), feed temperature change is taken into account. Also, each rule system must take into account whether the continuous phase is oil or water. If water is the continuous phase, oil droplets are dispersed throughout the water phase. If oil is the continuous phase water droplets are dispersed throughout the oil phase. The physical properties of the system, especially viscosity, strongly depend upon which phase is the continuous one.

As an example, *Fuzzy Soft Sensor 1* has 27 rules all with the same form that is described for the original 45 rules, but the membership functions have a much smaller range. All together there are approximately 700 rules in the combined fuzzy soft sensor.

NEURAL NETWORK SOFT SENSOR

A neural network (NN) was used to invert the computer model. Training and test sets for the NN were generated by randomly selecting values for $\phi_{w,a}$, $\phi_{w,b}$, $\phi_{s,a}$, $\phi_{s,b}$ (fixing all other inputs to the program) and limiting $\Delta\phi_{sw}$, $\Delta\phi_s$, and $\Delta\phi_w$ to between ±20%. The computer model was then used to compute ΔF and ΔP. A total of 41,757 cases were generated and randomly split between a training set (31,000 cases) and a test set (10,757 cases). The NN structure used was: backpropagation network with one hidden layer, extended delta-bar-delta learning rule, and tanh transfer function.

The first generation NN had three input nodes, $\Delta\phi_{sw}$, ΔF, and ΔP, and one output node, $\Delta\phi_w$. $\Delta\phi_s$ was calculated as $\Delta\phi_s = \Delta\phi_{sw} - \Delta\phi_w$. Hidden nodes were added until the optimum number were found. For the first generation network, five hidden nodes gave the best results. Three different objective function measures were used to determine the best NN when training and adding hidden nodes: correlation (r^2), root-mean-square error (E_{RMS}), and average absolute error (E_{abs}) between NN output and actual value.

In an attempt to get better results, a second generation NN was trained using $\Delta\phi_{sw,a}$, the initial feed BS&W, as an additional input node. Seven hidden nodes gave the best results for this NN. The structure and objective function measures of these two NN are summarized in Table II. The percentage of cases that were less than a given absolute error in $\Delta\phi_s$ or $\Delta\phi_w$ for each network is shown in Table III. It is obvious that the second generation NN gave better results. A closer examination of the data revealed that cases that the NN had problems with correspond to mixtures with very high solids content - an area where the physical property correlations in the computer program are least reliable.

TABLE II. Summary of structure and measures for two neural networks.

NN	Input nodes	Hidden Nodes	r^2	E_{RMS}	E_{abs}
1st Gen.	3	5	0.967	2.618	1.889
2nd Gen.	4	7	0.973	2.346	1.615

TABLE III. Comparison of results for two neural networks.

	Cases below Min. Abs. Error	
Minimum Absolute Error (%)	**1st Gen. NN**	**2nd Gen. NN**
1	39.1%	47.7%
2	64.5%	71.9%
3	80.9%	83.2%
4	89.1%	89.8%
5	93.6%	94.1%
6	96.2%	96.8%
7	97.7%	98.4%
8	98.5%	99.1%
9	99.1%	99.6%
10	99.5%	99.8%
11	99.7%	99.9%
12	99.9%	100.0%
13	100.0%	100.0%
14	100.0%	100.0%
15	100.0%	100.0%

More work needs to be done before the NN soft sensor can be used effectively in the centrifuge control system. Additional test cases need to be generated by varying the other centrifuge operating parameters (fractional power to the feed pump, hydrostatic head on pump, API gravity of the oil, heater efficiency, and the process temperature setpoint) in the computer model. Training a NN on this larger, more comprehensive, data will result in a more robust soft sensor. An auxiliary soft sensor is also needed for the cases where the heater is capacity-limited and is not able to maintain the process temperature setpoint with changing flow conditions. In this case, instead of an increased heater power requirement (to maintain the setpoint), a drop in the process temperature is observed. The computer model can be modified and an auxiliary NN can be trained on this subset of data.

COMPARISON OF SOFT SENSORS

Two approaches to developing a soft sensor have been explored. The first was a fuzzy rule-based system derived from an expert's knowledge of the flow system. This grew into a system of 27 different soft sensors when it was discovered that the initial system did not span the range of possible operating conditions. A computer model of the flow system was developed to aid in the creation of the 27 soft sensors. This approach worked about 85% of the time for the first instance and could probably be made to work near 100% with further development of the 27 soft sensors

The second approach was to develop a neural network that would basically invert the computer model. This approach worked about 94% of the time but is limited by our understanding of the underlying chemistry of special cases.

Both approaches show promise and best approach may be to use a neural network soft sensor that covers most cases and augment it with a fuzzy soft sensor that relies on expert knowledge for difficult cases.

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